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Smart Charging With Hourly Pricing as Policy Intervention: Reducing Costs and Grid Congestion for Promoting Electric Vehicles in Developing Countries

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ABSTRACT

This study deploys smart charging with hourly pricing to address grid congestion concerns associated with the anticipated growth of electric vehicles (EVs) in developing countries. We propose an optimization technique to establish an hourly pricing model for distribution companies, promoting off-peak charging behavior among EV owners. An agent-based energy management system, integrating grid-to-vehicle and vehicle-to-grid functionalities for optimized energy flow, is introduced to facilitate coordination between EV aggregators and the grid. The model is evaluated using real distribution network data with seasonal load variations. The results reveal that with 10% EV penetration, hourly pricing can significantly reduce charging costs for EV owners by about 30%. More importantly, it offers substantial relief for the grid by considerably reducing peak transformer load compared with flat or two-part tariffs. Using Pakistan as a case study of a developing country, this research demonstrates the potential of smart charging with dynamic pricing as a policy intervention for promoting EVs while mitigating utility grid congestion.

1 | Introduction

Due to continuously evolving environmental issues, there is a need to boost green technology. Concerns about conventional cars and energy sources are raised due to environmental and climate change issues [1]. The transportation sector significantly contributes to pollution worldwide due to its role in increasing levels of fine particulate matter (PM2.5), ozone, and nitrogen dioxide. As a result, researchers around the globe are concentrating on using renewable energy sources (RES) to power the transportation sector.

The popularity of electric vehicles (EVs) has grown due to environmental concerns regarding exhaust emissions and the insufficiency of petroleum resources. EVs are promising solutions for catering to environmental issues [2]. However, the growing use of plug-in electric vehicles (PEVs) in distribution power networks is causing many difficulties, for instance, distribution transformer stress, undesirable peaks, congestion in transmission lines, voltage violations, and growing system losses [3]. Issues like the high cost, deterioration of EV batteries, and the time needed for charging them should also be considered. Uncoordinated charging of EVs negatively impacts the grid, such as deteriorating the system's voltage profile [4]. Many studies have analyzed the impact of EVs on smart grids [5]. The vehicle-to-grid (V2G) network is impacted by various loading

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situations that affect voltage and power-sharing in the electrical network. Recent studies [6] investigate dynamic pricing–based coordinated EV charging to reduce peak demand and alleviate grid congestion under increasing EV penetration. Results show that time-varying tariffs and coordinated control significantly improve grid performance compared with flat charging schemes. Research [7] has analyzed the impact of EV integration on real-world distribution feeders using clustering techniques to select representative networks. Results show that smart-charging strategies such as time-of-use (TOU) and load balancing (LB) significantly reduce peak loading, transformer overloading, and infrastructure upgrade costs, with LB demonstrating superior performance at higher enrollment levels.

This research demonstrates the significant potential of smart charging with dynamic hourly pricing to address grid congestion and promote EV adoption in Pakistan. Combining an optimized energy pricing model, an agent-based energy management system, a stochastic placement model of EVs, and real distribution network data, the proposed solution offers cost savings for EV owners, mitigates grid strain during peak hours, and enables policy intervention against the uncertain growth of EVs.

1.1 | Literature Review

Outdated infrastructure and financial limits leading to inefficiencies and increased costs are among the major challenges faced by the power distribution companies (DISCOs) in Pakistan [8]. Therefore, carefully managing grid integration of promising technologies like EVs or solar photovoltaics (PVs) is critical to avoid overburdening the aging infrastructure of utilities in developing countries. A study in [9] proposes a policy framework to address technical and financial challenges in Pakistan's power distribution sector. The energy transition poses multiple technical, economic, and organizational issues. One key concern, particularly in zonal electricity markets, is how to manage future congestion management [10].

It is worth exploring the possibilities of using PEVs to provide auxiliary services to the distribution power grid in controlling active and reactive power [11]. A lot of researchers are working on various aspects of charging EVs. Control of the charging of PEV batteries is essential for integrating PEVs into the distribution grid and minimizing the impacts of widespread PEV adoption. V2G and grid-to-vehicle (G2V) technologies were mutually beneficial options for PEV owners and the grid operator. In G2V mode, extra electricity from the grid can be stored in the PEVs' batteries during off-peak hours. In the V2G mode of operation, PEVs can sell electricity back to the grid during the discharging phase [12]. Several studies have explored the effect of applying different electricity tariff designs and pricing methods in combination with V2G charging [13]. The growth of V2G interactions in China holds enormous promise for exploiting variable resources, especially EVs and energy storage with lithium-ion batteries, to boost grid flexibility and stability [14]. Study [15] presents a smart microgrid-integrated EV charging control framework that utilizes open charge point protocol (OCPP)-based communication and IEC 61850 architecture to dynamically manage fleet charging demand, mitigate distributed solar generation impacts, and address duck curve challenges through variable power control strategies.

Controlled EV charging has various potential benefits because charging can begin when electricity is inexpensive or energy from other renewable sources is offered. Moreover, EVs can power resident loads connected to the distribution network. In this method, the congestion in the electric transmission network is reduced and EV owners can make money [16]. With proper technology development and usage scenarios, V2G might play a crucial role in the new power system with RES as the main component, generating considerable profitability [17]. For energy management of EVs, multiple approaches have been discussed in the literature. These approaches include mathematical modeling, heuristic, statistical, practical utility approaches, market-based strategies, and agent-based modeling.

Heuristic and statistical approaches have also been reported in the literature. Integrated demand response was used to alleviate the congestion in the transmission and distribution network [18]. A heuristic energy management strategy was proposed in [19] to control multiple EVs in the presence of PV generators. An energy management strategy was proposed for a large EV charging station (EVCS) by chance-constrained programming and Monte Carlo simulation [20]. The optimal location of charging spots was proposed in [21] to alleviate the congestion in the distribution system, after running the load flow analysis using the Newton–Raphson method. A study in [22] presents an optimum combination of all three types of EV chargers for efficiently managing EV demand while minimizing installation costs, losses, and distribution transformer loading. The effects of PV generation are also considered in the analysis.

Practical utility approaches have been explored for mitigating congestion. A study in [23] discusses the effects of increasing EV adoption and the possibility of higher demand on the distribution system, which demands load optimization to maintain sustainable development. Peak shaving can be used to provide LB when using EVs as energy storage devices [24]. To overcome the uncoordinated charging problem and to avoid the peak load a study was performed for charging EVs during the off-peak time to fill the demand valley and clip the peak load by discharging EVs during peak hours [25]. Using the day-ahead framework, an optimization algorithm was proposed for the optimum charging of EVs by using the charging data from a real-world pilot program [26]. By using TOU pricing, optimal charging was scheduled by connecting reactive power-compensating devices in the system to maintain the voltage profile [27].

Some researchers have discussed market-based approaches for the energy management of EVs. An algorithm was proposed in [28] to prevent line congestion by motivating EV aggregators, to actively participate in the market. In [29], an algorithm was proposed by considering the EV aggregators, distributed generation, and market operators to alleviate the congestion in the distribution system. Researchers suggested a framework for deregulated market participation where participants using RES are urged to assist the system to reduce congestion.

Agent-based modeling has been discussed in reference [29] to handle the energy for EVs and EVCSs. The system operator acted as the master decision maker while EVs and EVCSs worked as independent decision makers to handle their energy scenarios. EVs and EVCSs wanted to maximize their financial profit while the system operator indirectly controlled their energy scenarios to maintain the system constraints. GAMS software was used to implement this optimization process. Multiagent selfish collaborative architecture was proposed in [30]. A multiagent multiobjective reinforcement learning architecture was designed to facilitate EV charging while reducing energy bills and preventing transformer overloads.

Many studies analyze the effect of EV charging on operating costs and grid conditions under different pricing regimes and propose various pricing strategies for effective management. Recent studies have proposed dynamic pricing mechanisms for coordinated EV charging to mitigate grid congestion and reduce charging costs under rising EV penetration, using optimization-based or agent-based frameworks to guide user charging behavior through time-varying tariffs. Simulation results consistently show that such coordinated pricing strategies reduce peak demand and improve overall grid performance compared with flat or static tariff schemes [31]. In [32], an EVCS and aggregator coordinate without exchanging or disclosing private information. The merits of the suggested model are demonstrated by a numerical analysis that shows an overall 78.3% drop in costs. Fang et al. [33] developed a bilevel dynamic pricing framework that links power and transportation networks by deriving locational marginal prices through optimal power flow (OPF) and determining charging station prices via a noncooperative game. Their results show improved charging station utilization and higher renewable energy integration compared with flat and TOU tariffs. Analysis in [34] reports a 10% reduction in overall costs for the state of California. The findings indicate that smart charging with TOU rates for expanded daytime periods is the policy most likely to progress California's dual PEV and RE targets. A study [35] proposes a bilevel optimization model for dynamic EV charging pricing, where a charging provider sets time-varying prices while customers select charging options based on preference lists and reserve prices. The results show that the model effectively balances profit maximization and peak load reduction through a mixed-integer linear reformulation. Anjos et al. [36] developed a bilevel dynamic pricing framework that incorporates heterogeneous customer preferences and reserve prices to optimize charging station profits while mitigating grid peaks. Computational results demonstrate that the proposed reformulation efficiently solves large-scale instances and achieves significant peak demand reduction.

The reviewed literature highlights the environmental necessity of transitioning to EVs while addressing their adverse impacts on power grids, particularly in developing countries with aging infrastructure [8, 9]. Studies cover diverse EV energy management approaches, including mathematical, heuristic, statistical, practical utility, market-based, and agent-based methods, often focusing on mitigating congestion, optimizing charging, and integrating renewable sources [11, 12, 17]. However, research gaps remain in developing context-specific models that combine optimized dynamic pricing with coordinated V2G and G2V operations for both cost reduction and congestion alleviation. Our research addresses this gap by proposing an hourly pricing model integrated with agent-based smart charging, validated using real network data to reduce costs for EV owners and relieve grid stress in developing countries.

While several recent studies have explored real-time dynamic pricing, deep reinforcement learning, and large-scale V2G integration, such approaches typically assume mature electricity markets and advanced digital infrastructure. In contrast, this study proposes a day-ahead hourly pricing framework tailored to developing economies where flat or two-part tariffs remain applicable. The proposed framework serves as a transitional and feasible step between conventional tariff structures and fully dynamic real-time markets, thereby providing foundational building blocks for progressive smart-charging deployment.

1.2 | Research Contribution

Recent literature has extensively explored dynamic EV pricing mechanisms incorporating deep reinforcement learning, bilevel optimization, congestion-based tariffs, and large-scale V2G integration. However, most of these studies assume mature wholesale electricity markets, high smart-meter penetration, established ancillary service markets, and advanced digital communication infrastructure. Nevertheless, such assumptions do not hold in many developing economies, including Pakistan, where flat or two-part tariffs remain applicable, and an hourly pricing market does not exist.

This study contributes by:

1. Proposing a day-ahead OPF–derived hourly pricing mechanism as a transitional step towards wholesale/retail real-time market pricing.
2. Integrating real distribution feeder data representative of a developing-country context.
3. Developing a three-layer agent-based coordination model tailored to institutional realities.
4. Quantifying transformer loading and congestion impacts under early-stage EV penetration by *K*-Means clustering.
5. Aligning the pricing mechanism with ongoing regulatory reforms, in view of emerging and anticipated competitive electricity markets.

Rather than pursuing highly sophisticated real-time market optimization, this work establishes practical and scalable building blocks for progressive smart-charging implementation in developing economies. The framework offers a transitional hourly pricing signal to bridge the gap between existing conventional tariff systems and future dynamic market structures.

1.3 | Paper Organization

This paper is organized as follows: Methodology is presented in Section 2, Section 3 describes the case studies, Section 4 offers the detailed results and discussion of the research, followed by Conclusion and Policy Recommendation in Section 5.

2 | Methodology

The proposed work includes energy management of EVs at minimum cost and congestion management of the power system. The methodology involves estimating the state of charge (SOC) of EVs upon their return for charging in a residential feeder. Grid connectivity of EVs is modeled by real network data from an urban residential feeder. Since only peak load data is offered by the utility for the feeder, typical hourly summer and winter load profiles are synthesized from national seasonal load curves. The OPF is run on a reduced 114-bus model of the national grid to discover the hourly price signal for this research. Agent-based modeling of EV aggregators enables their private decision-making based on their interactions with vehicle owners and utility operators. Smart charging can be implemented without significant hardware modifications when software-enabled chargers, existing smart meters or basic advanced metering infrastructure (AMI), and standard cellular or internet communication networks are already available, allowing coordination primarily through pricing signals and cloud-based control.

Full-scale V2G participation in ancillary service markets is deliberately excluded from the present scope. Given the increasing penetration of distributed solar PV and emerging reverse power flow challenges in Pakistan's distribution network, the current operational priority is load management rather than bidirectional energy trading.

This research methodology is further explained in the following four subsections.

2.1 | SOC Estimation

The "cubic capacity" of the engine in a conventional vehicle is measured in centimeter cubes (cc). Therefore, the vehicle data set published in [22] contains cc ratings of the conventional vehicles. Using online information about EV batteries, the cc of vehicles is converted into the battery capacity for EVs. EVs' load on the feeder depends on the final SOC when vehicles return home. However, since the data set [22] is for conventional vehicles, it lacks data on the final SOC of EVs. Therefore, calculations for the final SOC of the EVs are carried out by using a formula proposed in [37].

The SOC estimation model is based on typical daily travel demand assumptions and battery capacity parameters representative of commercially available EVs. The charging requirement is computed from arrival SOC and desired departure SOC, ensuring consistency with user mobility needs while enabling tariff-responsive scheduling.

The charging and discharging rate of EVs is considered 1.9 kW according to the specification of level-I chargers [38]. Since we are proposing a solution for a typical residential feeder, EVs returning home in the evening need overnight charging to be ready for the next day. Therefore, the final SOC is required as input for the proposed algorithm to devise the least cost overnight charging schedule according to the requirements of the EV owners. A uniform residential charging power level is assumed to reflect prevailing charger ratings currently available in the local market. Although heterogeneous charging capacities may influence feeder stress differently, this simplification allows controlled comparison between tariff mechanisms while preserving the representativeness of early-stage adoption conditions.

The potential impact of battery degradation is not explicitly incorporated into this study, as its marginal effect on the results is expected to be limited under the proposed operating conditions. The analysis assumes a smart-charging strategy based on hourly electricity pricing, which inherently promotes operational behaviors that help mitigate battery degradation. These behaviors include predominantly shallow cycling rather than deep discharge cycles, lower average C-rates due to controlled charging power levels, and reduced exposure to high-temperature conditions by avoiding peak-hour charging periods. These factors are well established in the literature as key determinants in slowing battery deterioration. Nevertheless, a more comprehensive techno-economic assessment could explicitly incorporate battery degradation through a Levelized Cost of Storage (LCOS) framework, allowing for a more precise quantification of lifecycle impacts.

2.2 | Real Feeder With Synthesized Load

Security and privacy policies regulating critical infrastructure data can restrict researchers from accessing data of real power systems, but data access is essential for technical development [39]. Some standardized networks, such as the IEEE Transmission and Distribution test cases, have been widely utilized by academics for decades. More recently, researchers have tried to generate synthetic distribution systems, but studies involving real distribution system data are not common.

A model of the Gulshan-e-Iqbal distribution feeder of LESCO is used for this research work. All system parameters, such as conductor specifications, buses, and transformers, are similar as reported in [9]. However, the load of the feeder is synthesized from data of typical summer and winter load profiles of Pakistan reported in the State of Industry Report published by NEPRA in 2019.

LESCO has provided the load data for the Gulshan-e-Iqbal feeder only for the peak hours that are utilized in [38, 40]. Using typical summer and winter season load variations in Pakistan, 24-h load curves shown in Figure 1 are constructed for the Gulshan-e-Iqbal feeder for the summer and winter seasons. It is observed that during the summer season, peak demand occurs at 01.00, and during the winter season, peak demand occurs at 19.00.

2.3 | Proposed Price

In Pakistan, DISCOs offer a Flat Rate to most residential customers connected by single-phase meters and a two-part Tariff to the minority provided by three-phase meters. Prices considered in this research are 37.8 Rs/kWh as the Flat Rate, whereas 35.57 and 41.89 Rs/kWh as the two-part Tariff of LESCO for off-peak time and on-peak time, respectively, as reported on the LESCO website. However, since hourly variable pricing signals do not currently exist, OPF is run on a reduced 114-bus model of the national grid to find a new Hourly Price for this research. The resulting Hourly Price curves for the summer and winter seasons are shown in Figures 2 and 3, respectively.

The hourly EV charging prices are determined through an OPF framework that captures system-wide operational costs under network and generator constraints. Equation (1) presents the mathematical formulation of the objective function, and Equations (2)–(7) represent the associated cost components considered in the optimization model.

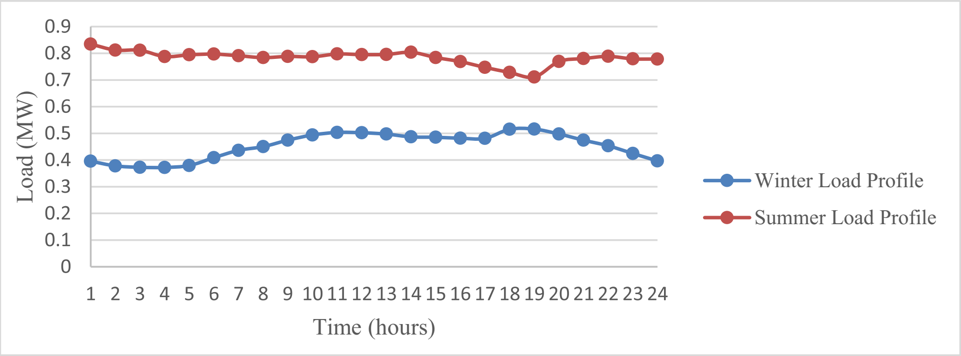


FIGURE 1 | Load profile of Gulshan-e-Iqbal feeder.

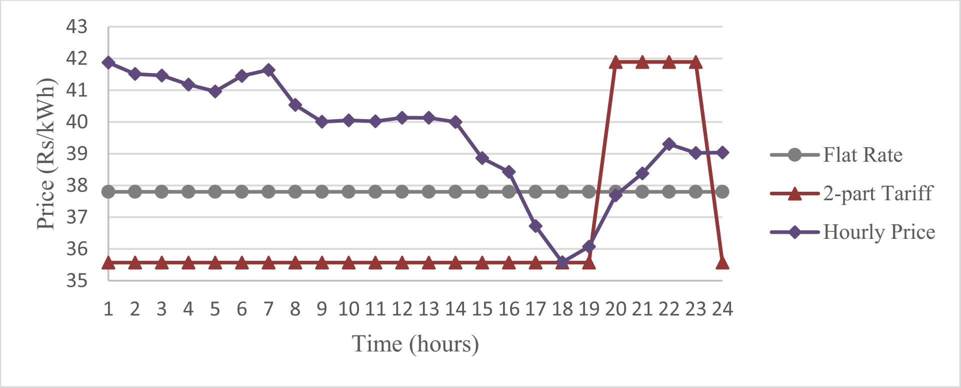


FIGURE 2 | Price during the summer season.

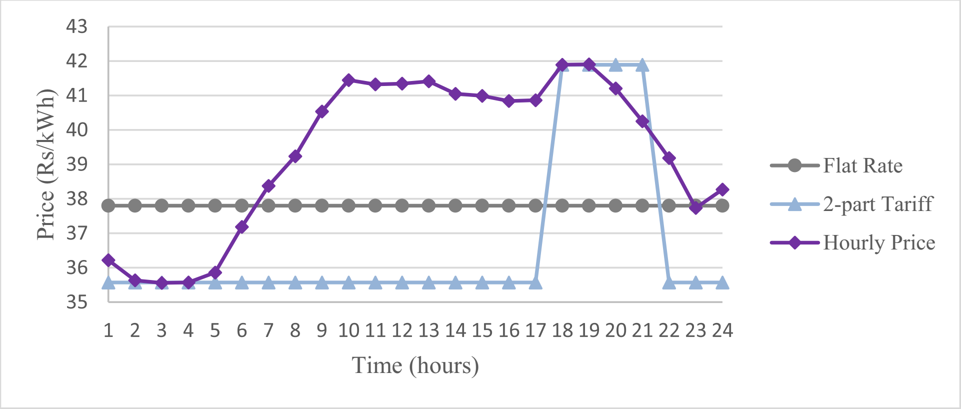


FIGURE 3 | Price during the winter season.

$$\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{f}_{\boldsymbol{p}}(\boldsymbol{p}, \boldsymbol{p}_+, \boldsymbol{p}_-) + \boldsymbol{f}_{\boldsymbol{r}}(\boldsymbol{r}_+, \boldsymbol{r}_-) + \boldsymbol{f}_{\delta}(\boldsymbol{p}) + \boldsymbol{f}_{\boldsymbol{lf}}(\delta_+, \delta_-) + \boldsymbol{f}_{\boldsymbol{uc}}(\boldsymbol{v}, \boldsymbol{w}). \tag{1}$$

Each of the five components is elaborated individually as follows:

1. Expected energy cost (power dispatch and redispatch)

$$\boldsymbol{f}_{\boldsymbol{p}}(\boldsymbol{p}, \boldsymbol{p}_+, \boldsymbol{p}_-) = \sum_{t\in T}\sum_{j\in J^t}\sum_{k\in K^{tj}} \vartheta_{\alpha}^{tjk} \sum_{i\in I^{tjk}} \left[C_P^{ti}\left(p^{tijk}\right) + C_{P+}^{ti}\left(p_+^{tijk}\right) + C_{P-}^{ti}\left(p_-^{tijk}\right) \right], \tag{2}$$

where probability ϑ^{tjk} of contingency k in scenario j at time t adjusted for α.

$$\vartheta_{\alpha}^{tjk} = \begin{cases} \vartheta^{tj0} + \alpha \sum_{k\in K^{tj}} \vartheta^{tjk}, & k = 0, \\ (1-\alpha)\vartheta^{tjk}, & \forall\ k \in K^{tj} \neq 0. \end{cases} \tag{3}$$

2. For rare scenarios, the cost of contingency reserves for both upward and downward scenarios:

$$\boldsymbol{f}_{\boldsymbol{r}}(\boldsymbol{r}_+, \boldsymbol{r}_-) = \sum_{t\epsilon T} \gamma^t \sum_{i\in I^t} \left[C_{R+}^{ti}\left(r_+^{ti}\right) + C_{R-}^{ti}\left(r_-^{ti}\right) \right]. \tag{4}$$

3. Load following ramping (Expected wear and tear cost),

$$\boldsymbol{f}_{\delta}(\boldsymbol{p}) = \sum_{t\in T} \gamma^{t} \sum_{\substack{j_1 \in J^{t-1} \\ j_2 \in J^{t}}} \varphi^{tj_2 j_1} \sum_{i\in I^{tj_2 0}} \boldsymbol{C}_{\delta}^{i} \left(\boldsymbol{p}^{tij_2 0} - \boldsymbol{p}^{(t-1)ij_1 0} \right). \tag{5}$$

4. The costs of ancillary service (load following reserve) in scenarios with a high likelihood of occurrence,

$$\boldsymbol{f}_{lf}(\delta_{+}, \delta_{-}) = \sum_{t\in T} \gamma^{t} \sum_{i\in I^{t}} \left[\boldsymbol{C}_{\delta_{+}}^{ti}\left(\delta_{+}^{ti}\right) + \boldsymbol{C}_{\delta_{-}}^{ti}\left(\delta_{-}^{ti}\right) \right]. \tag{6}$$

5. Unit commitment (startup and shutdown costs),

$$\boldsymbol{f}_{uc}(\boldsymbol{v}, \boldsymbol{w}) = \sum_{t\in T} \gamma^{t} \sum_{i\in I^{t}} \left(\boldsymbol{C}_{v}^{ti} \boldsymbol{v}^{ti} + \boldsymbol{C}_{w}^{ti} \boldsymbol{w}^{ti} \right). \tag{7}$$

Beyond the objective formulation, the OPF incorporates key operational constraints to ensure secure and feasible system operation. These include power balance requirements to match generation with demand at each time interval, transmission capacity limits to respect network thermal ratings, and voltage magnitude limits to maintain acceptable operating conditions. Generator operational constraints are also enforced, including generation limits, ramping capabilities, reserve obligations, and minimum up/down time requirements. Finally, integrality conditions preserve the discrete nature of commitment decisions within the mixed-integer linear programming (MILP) structure. Together, these constraints ensure that the derived hourly prices reflect both economic efficiency and system reliability considerations.

Figure 2 shows that during the summer season for the Hourly Price case, the price is highest at 01.00 h and for the two-part tariff case peak hours are from 19.00 to 23.00. Figure 3 indicates a new trend for the Hourly Price case during the winter season, as the maximum price occurs at 19.00 during the peak hours from 17.00 to 21.00 for the two-part case. The flat rate remains the same for both seasons.

2.4 | Agent-Based Modeling

The proposed work for the energy management of EVs to mitigate the congestion of the power system is tested over the 11 kV feeder of Gulshan-e-Iqbal LESCO. The feeder has 60 transformers of different kVA ratings. This work involves programming in Python by using Anaconda Jupyter Notebook, whereas the feeder is designed using Pandapower libraries. Load flow studies have been performed by using the Newton–Raphson algorithm. The planning departments of all DISCOs in Pakistan use Synergy software. After extracting the.kmz file of the Gulshan-e-Iqbal feeder from the Synergy software, it was loaded into Google Earth to visualize the route of the feeder. Figure 5 shows the resulting street layout of the Gulshan-e-Iqbal feeder on a Google map. The feeder, managed by a utility operator, is divided into six zones as shown in Figure 5 each managed by an EV aggregator. The formula used to calculate the number of EVs is given below:

$$\mathrm{EV}_{\mathrm{Load}} = \%\text{age EV Penetration} * \text{Maximum Load on the Feeder}, \tag{8}$$

$$\text{Total EVs} = \text{round}\left(\frac{\text{EV Load}}{1.9\,\text{kW}} \right). \tag{9}$$

From Equation (9), for 5% and 10% penetrations, 23 and 46 EVs have been considered, respectively. Here, 5% EV penetration means 5% of the total load over the feeder. The number of EVs for each zone is selected based on the number of nodes in each zone and placed randomly. EVs connected in each zone convey their information to their relevant aggregator, and the utility operator provides information related to the loading of transformers and the tariff to all six EV aggregators. When the utility operator conveys the information regarding the loading conditions and the tariff to the EV aggregator, it has the private information of all the EVs connected in its zone. Therefore, the EV aggregator develops the optimal charging schedule for its EVs to mitigate high loading conditions while charging at the least cost.

To operationalize the hourly pricing mechanism, a three-layer agent-based framework is developed. The operational logic of the proposed agent-based coordination mechanism is illustrated in Figure 4. The framework consists of three interacting layers, the utility agent, the aggregator agent, and multiple EV user agents. The utility agent performs day-ahead load forecasting and solves an MILP-based OPF to generate hourly price signals. These price signals are communicated to the aggregator agent, which collects EV-specific parameters (arrival time, departure time, battery capacity, and initial SOC) and optimizes the aggregated charging schedule subject to transformer capacity constraints. The optimized schedules are then communicated to individual EV users, who confirm charging based on cost and mobility requirements. A feedback loop from the aggregator to the utility enables monitoring of feeder loading conditions, ensuring coordinated charging while preserving network security.

This hierarchical coordination allows decentralized decision-making while preserving feeder-level stability. Although large-scale real-world deployment is not yet implemented in Pakistan, the framework enables forward-looking impact assessment under realistic institutional conditions.

From an infrastructure planning perspective, transformer upgrades primarily resolve localized capacity constraints, whereas hourly pricing infrastructure delivers system-wide congestion management and operational flexibility. At low EV penetration levels (e.g., < 10% per feeder), targeted transformer reinforcement may appear more cost-effective. However, as EV adoption becomes spatially widespread, repeated upgrades across multiple nodes become increasingly capital-intensive. In contrast, leveraging existing and emerging AMI, dynamic hourly pricing distributes costs system-wide and over time. Consequently, beyond moderate EV penetration levels, operational solutions based on dynamic pricing are likely to become more economical than recurrent physical network reinforcements, particularly in large urban centers expected to host the majority of future EV uptake.

3 | Case Studies

Most residential customers are supplied by single-phase meters at a Flat Rate, whereas the minority served by three-phase meters get a two-part Tariff. However, since hourly

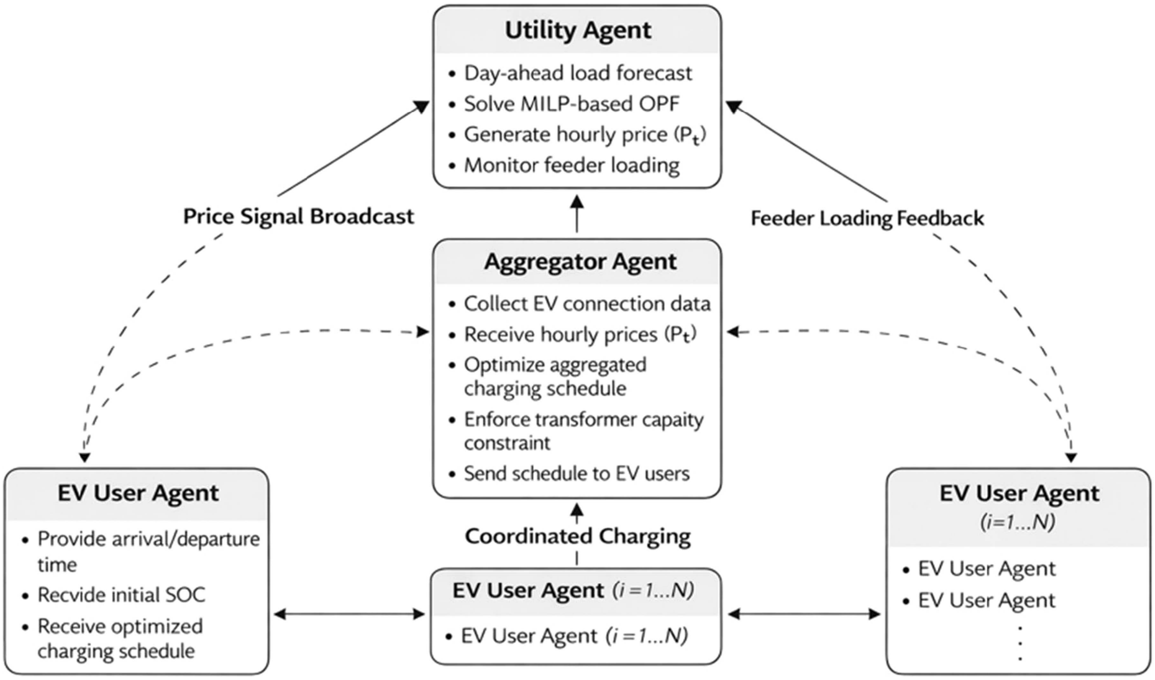


FIGURE 4 | Agent coordination framework. EV, electric vehicle; MILP, mixed-integer linear programming; OPF, optimal power flow; SOC, state of charge.

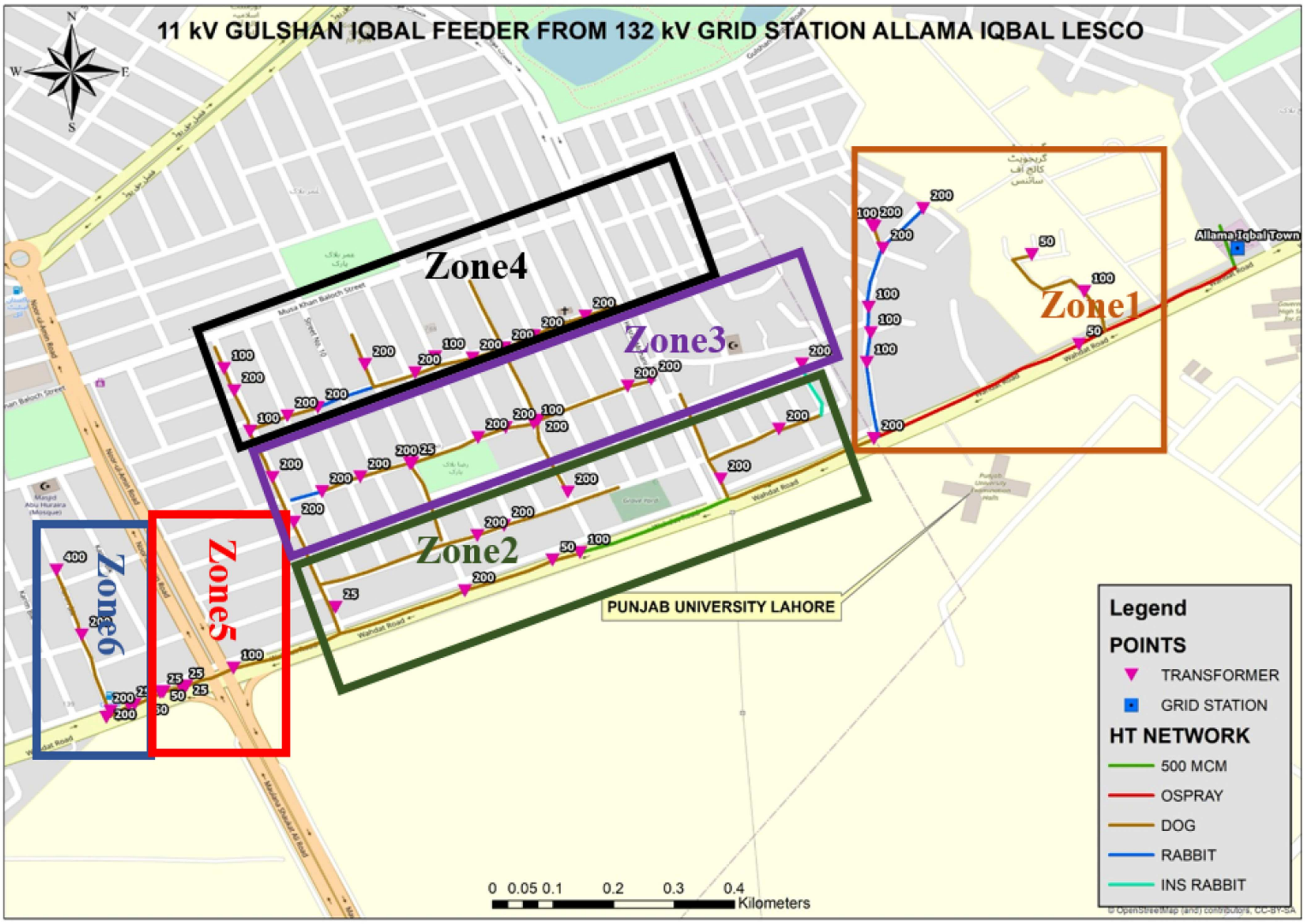


FIGURE 5 | Six zones in Gulshan-e-Iqbal feeder.

variable pricing signals do not currently exist, OPF is run on a reduced 114-bus model of the national grid to find a new Hourly Price for this research. Therefore, this work presents three case studies for a residential feeder: Flat Rate, two-part Tariff, and Hourly Price. A model of the Gulshan-e-Iqbal distribution feeder is used for this research because LESCO provided its data as a typical urban residential feeder. It is assumed that owners of the EVs return home between 4 p.m. and 9 p.m. The number of EVs returning home for each hour, formulated using the MATLAB curve fitting tool, is given by Equation (10).

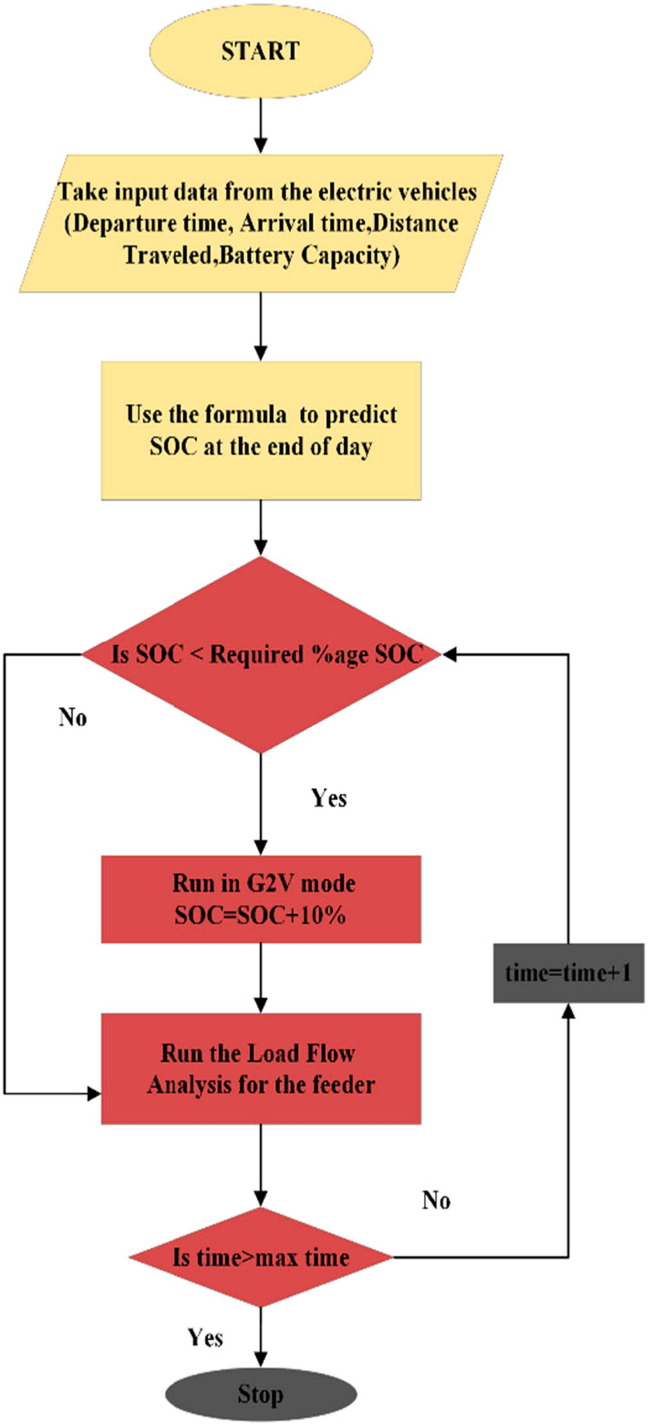


FIGURE 6 | Flowchart for flat rate. G2V, grid-to-vehicle; SOC, state of charge.

$$\mathrm{EV}(x) = \frac{1}{1.668\sqrt{2\pi}} \exp^{-0.5\left(\left(\frac{x-18.5}{1.668}\right)^2\right)}. \tag{10}$$

The selected EV penetration levels (5% and 10%) reflect realistic near-term adoption trajectories in Pakistan, where EV uptake remains at an early stage while distribution networks exhibit structural limitations.

Figure 6 shows that in the case of Flat Rate, the EV owners connect their vehicles as soon as they return home. Due to the Flat Rate, they do not consider loading conditions or the peak time of the load. Therefore, the system may experience heavy loading and consequently congestion in the power system.

In the second case of the two-part Tariff, the price of electricity is high from 6 p.m. to 11 p.m. Consequently, vehicle owners do not charge their vehicles right away upon returning home, as shown in Figure 7. Instead, vehicle owners with adequate SOC communicate with their aggregator upon reaching home. In the meantime, aggregators get the status of network conditions from the utility side. Therefore, the aggregator has information

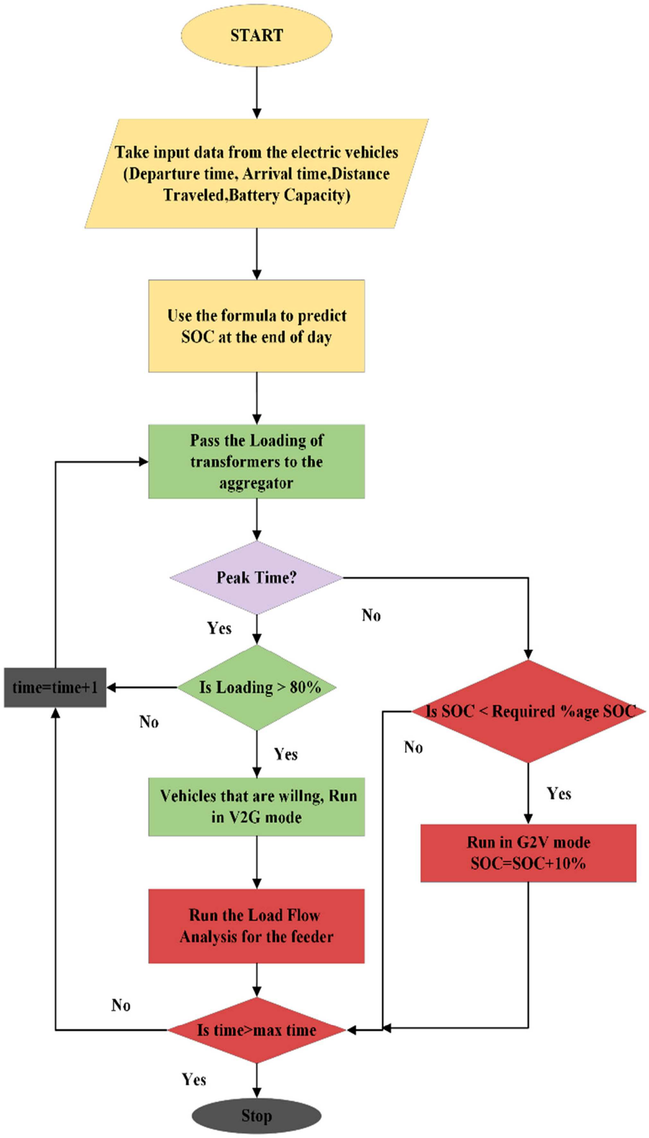


FIGURE 7 | Flowchart for two-part tariff. G2V, grid-to-vehicle; SOC, state of charge; V2G, vehicle-to-grid.

on network conditions and the SOC of EVs. Generally, EV owners tend to charge vehicles at a low price, for example, from solar PV in the afternoon, and wish to discharge at a higher evening peak price, for example, when transformers are loaded above 80%. Consequently, in such scenarios, the aggregator communicates to the utility operator and discharges the vehicles' batteries in V2G mode, mitigating feeder overloading and improving voltage that benefits both the utility and customers.

In the last case, an Hourly Price is proposed for energy management by using both V2G and G2V modes, as shown in Figure 8. In this case, when the EV owners return home, they inform their aggregator about their charging requirement for the next day. Since all the vehicles do not have to achieve 100% charging, they are charged according to their next-day requirements. The algorithm finds the least cost hours according to the charging requirement of EVs. This enables EV aggregators to develop charging schedules for EVs to achieve the least-cost operation.

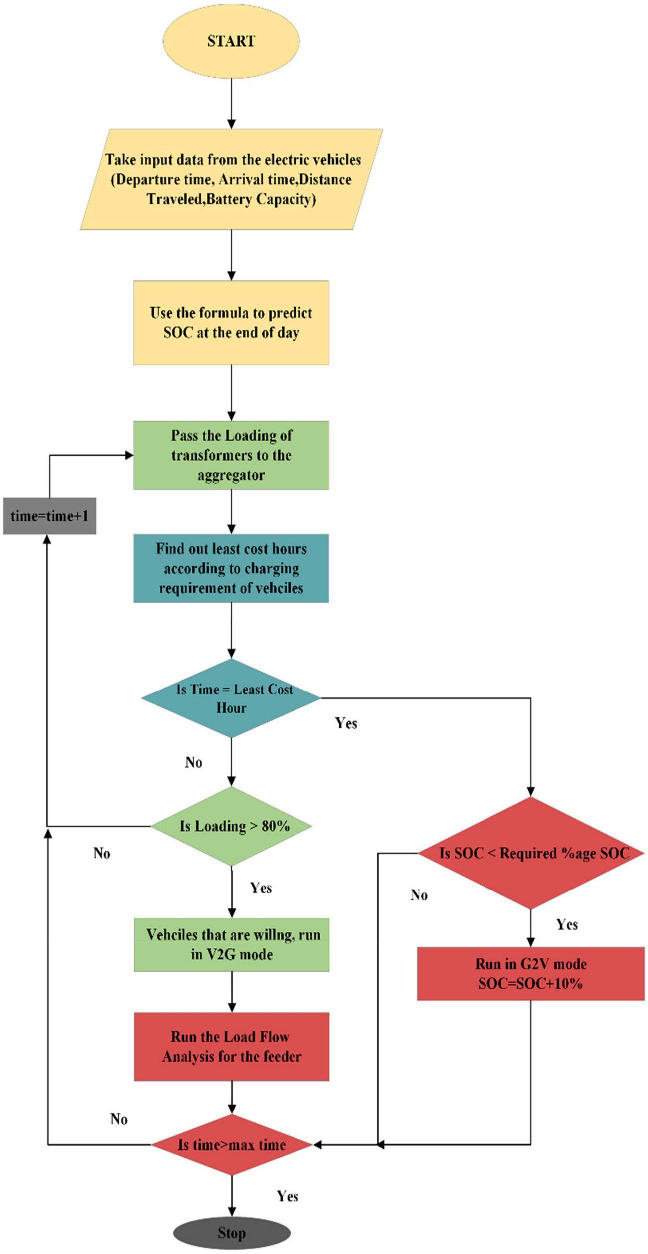


FIGURE 8 | Flowchart for hourly price. G2V, grid-to-vehicle; SOC, state of charge; V2G, vehicle-to-grid.

4 | Results and Discussion

The results of our research are presented and discussed as follows.

4.1 | Variation in Transformer Loading Under Alternative Pricing Regimes

The transformer loading condition of the Gulshan-e-Iqbal feeder with different penetrations of EVs has been analyzed. During the summer season from base case results, when no EVs were connected to the system, three nodes (21, 27, and 32) were observed as weak nodes. During the winter, the base load is less than that of the summer season. In the winter season, only two nodes (21 and 27) have been identified as weak nodes, their loading increases up to 80% during some hours when EVs are connected to the system.

The detailed loading conditions for two selected nodes are presented here for brevity. *K*-Means clustering indicated three clusters representing the rest of the system. The number of nodes in each cluster for the summer and winter seasons is presented in Table 1.

Cluster 1 for the summer season in Table 1 indicates the nodes whose loading is less than 10%. Cluster 2 consists of nodes with a transformer loaded between 30% and 40%, whereas Cluster 3 includes nodes loaded beyond 50%. Table 1 indicates nine nodes in the feeder whose loading increases beyond 50% during the summer season.

During the winter season, Cluster 1 in Table 1 indicates the nodes whose loading is less than 10%. Cluster 2 includes nodes with loading between 20% and 30%, whereas Cluster 3 consists of nodes with transformer loading beyond 40%. It is observed that most of the nodes in the winter season are lightly loaded. There are just 5 nodes in the feeder whose loading increases beyond 40% in winter.

4.1.1 | 5% and 10% EV Penetration

Using the predicted SOC, EVs' charging schedule is designed for a two-part Tariff and Hourly Price. EVs were randomly connected at different nodes, out of the 60 load nodes. Then nodes 21, 27, and 32 were identified as three weak nodes of the feeder. As shown in Table 2, Node 21 lies in zone 2 and the rating of its transformer is 25 kVA. Node 27 is present in zone 3, and the rating of the transformer connected there is also 25 kVA. Moreover, a 25-kVA transformer is connected at node 32 in zone 5. By connecting EVs over these nodes, transformer loading gets very high as they are heavily loaded even in the base case.

Since it is reported in [38] that there is no congestion in the distribution lines of this feeder, the focus of this work is on the management of charging and discharging the EVs in the distribution feeder while considering the congestion of the distribution transformers.

TABLE 1 | Clusters data for transformer loading during summer and winter seasons.

Cluster	Number of nodes during summer season	Transformer loading condition during summer season	Number of nodes during winter season	Transformer loading condition during winter season
1	44	< 10%	45	< 10%
2	7	Between 30% and 40%	10	Between 20% and 30%
3	9	More than 50%	5	Between 40% and 50%

TABLE 2 | Clusters data for per-unit voltage during summer and winter seasons.

Cluster	Number of nodes during the summer season	Per-unit voltage during the summer season	Number of nodes during the winter season	Per-unit voltage during the winter season
1	192	0.97–0.98	190	0.98–0.99
2	28	< 0.95	25	< 0.95
3	81	1–1.01	86	1–1.01

Table 2 depicts the transformer loading results of node 21 for all three case studies. This node is selected because it is heavily loaded even in the base case when no EV is connected. Transformers that are operating within the prescribed limits of 80% loading are indicated by green color. Yellow color depicts transformers that operate between 80% and 100%. The red indicates hours when the transformers start operating beyond 100% of operational limits. In Figure 9a, for the Flat Rate, the 0.8 p.u. threshold limit of the transformer is violated because vehicle owners have no incentive to change their charging patterns. In the case of a two-part Tariff, transformer loading dropped within limits between 19.00 and 23.00. EV owners with sufficient charge will discharge to get a high energy price, and consequently, transformer loading will drop within the limits. In case of an hourly varying price of electricity, the EV aggregator decides whether to charge or discharge for each hour. EV owners returned home in the evening, and their vehicles started charging as the price of electricity during these hours is low, as observed in Figure 9a. During late night hours from 1 a.m. to 7 a.m. electricity price is high, and consumers can discharge their vehicles to mitigate congestion as observed from the Hourly Price bars in Figure 9a. During daytime hours from 8 a.m. to 4 p.m., EVs are not available at home so, during these hours power transformers are violating the limits even in the Hourly Price case as shown in Figure 9a. Moving from 5% to 10% penetration increases the violation of limits, as indicated by the greater height of the red bars in Figure 9b. Since the rating of this transformer is just 25 kVA, it is essential to upgrade this transformer to cater to the anticipated load of EVs.

Figure 9c illustrates the transformer loading for 5% EV penetration during the winter season. During some hours, when the EV owner returns home transformer loading is greater than 80% in the case of Flat rate and two-part tariff as it is the peak loading time, when EVs get connected to the system during these hours transformer loading increases, however for the hourly price case during peak loading hours, transformer loading remains less than 80% even for the 10% EV penetration as depicted in Figure 9d. A major difference is observed during the summer and the winter charging pattern in the case of a two-part tariff, as peak hours are different in both cases. For the summer season in the two-part tariff case, peak hours are from 19.00 to 23.00, and loading decreases as shown in Figure 9a,b, during the winter season peak hours are from 17.00 to 21.00, as shown in Figure 8c,d.

In Figure 10, node 27 results have been presented. It shows that this node has a better condition as compared with the previous node. The limits that are violated in the Flat Rate and two-part Tariff are greater as compared with the Hourly Price case, depicted by the height of red bars in Figure 10a. For Flat Rate, transformer loading increases from 16.00 to 21.00. For the two-part Tariff case, loading behavior differs from the Flat Rate. As transformer loading increases between 16.00 and 19.00 and peak hours, vehicles are discharged to overcome the congestion or get the financial benefit of the high price in those hours. From 23.00 onwards again vehicles get charged. For 10% penetration, as shown in Figure 10b, the violation of limits gets increased as more numbers of EVs are getting connected. Figure 10c,d shows the transformer loading condition during the winter season. Similar behavior has been observed as of the previous node for Flat rate and two-part tariff. For the hourly price case, loading increases during late-night hours as prices get reduced.

4.2 | Voltage Profile of Feeder

Since there are 301 nodes in the Gulshan-e-Iqbal feeder, it is not feasible to represent the voltage condition of every node. On the basis of the distribution code threshold of 0.95 p.u. for under voltage and 1.05 for over voltage, no node violates the overvoltage limit during the summer and winter. *K*-Means clustering reveals that three clusters adequately represent the variety of voltage conditions in the feeder.

As shown in Table 2, Cluster 1 indicates the nodes whose per-unit voltages range from 0.97 to 0.98 p.u. Cluster 2 consists of the nodes whose per-unit voltages violate the under-voltage

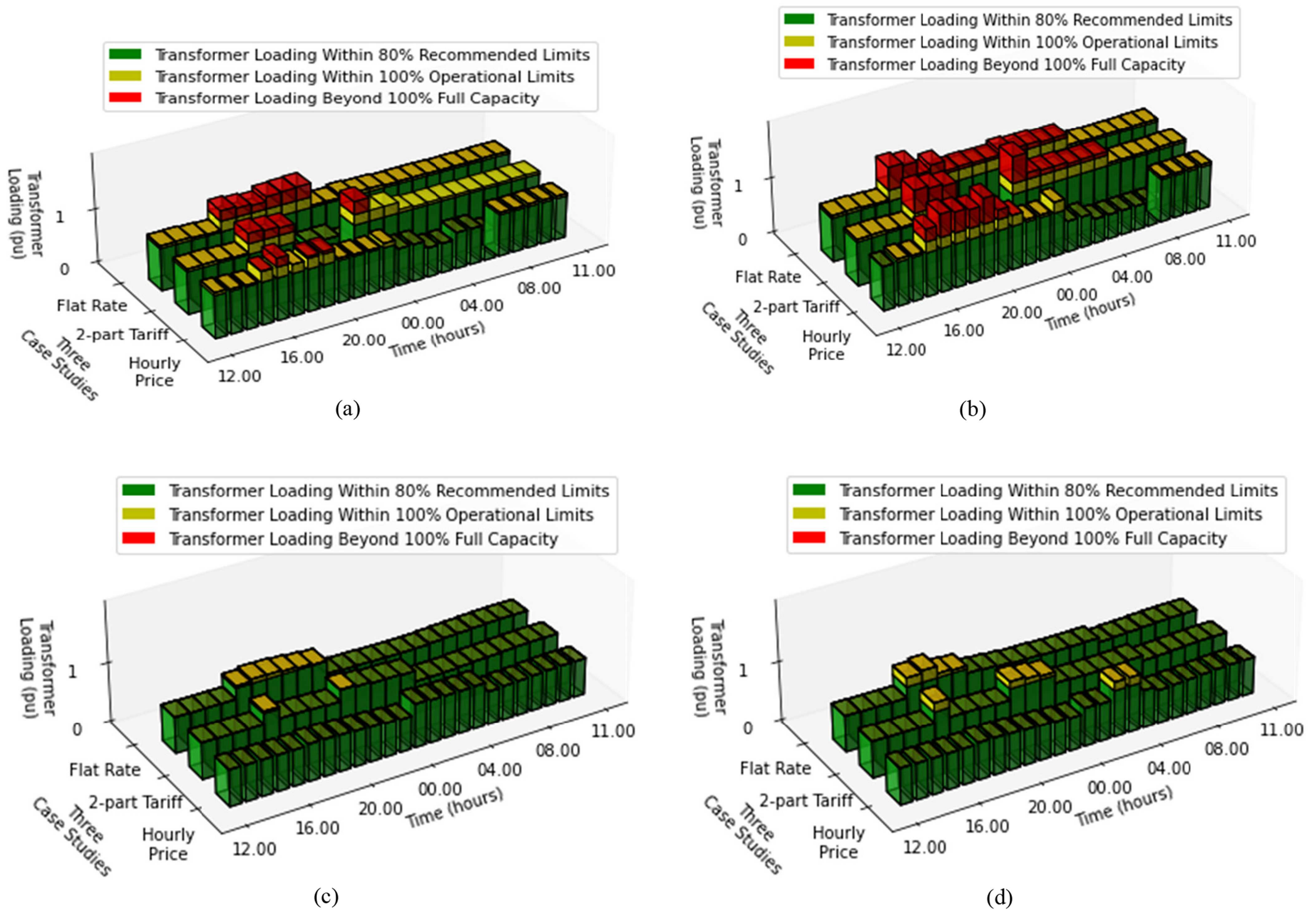


FIGURE 9 | Transformer loading percentage at node 21: (a) 5% EV penetration during summer, (b) 10% EV penetration during summer, (c) 5% EV penetration during winter, and (d) 10% EV penetration during winter. EV, electric vehicle.

limit of 0.95 p.u. Cluster 3 includes the nodes whose per-unit voltages are above 1 p.u. but not greater than the upper-voltage limit of 1.05 p.u. During the winter season, the use of *K*-Means clustering identifies that three clusters represent the condition of the feeder. During the winter season, Cluster 1 in Table 2 indicates the nodes whose per-unit voltages are in the range of 0.98 to 0.99 p.u. Cluster 2 includes the nodes whose per-unit voltages violate the under-voltage limit of 0.95 p.u. Cluster 3 indicates the nodes whose per-unit voltages are above 1 p.u but not greater than the upper-voltage limit of 1.05 p.u. It is observed that most of the nodes in the winter season are within safe voltage operating limits. Only 25 nodes are violating the under-voltage limit.

4.3 | Effect of Alternative Pricing Regimes on the Cost of EVs

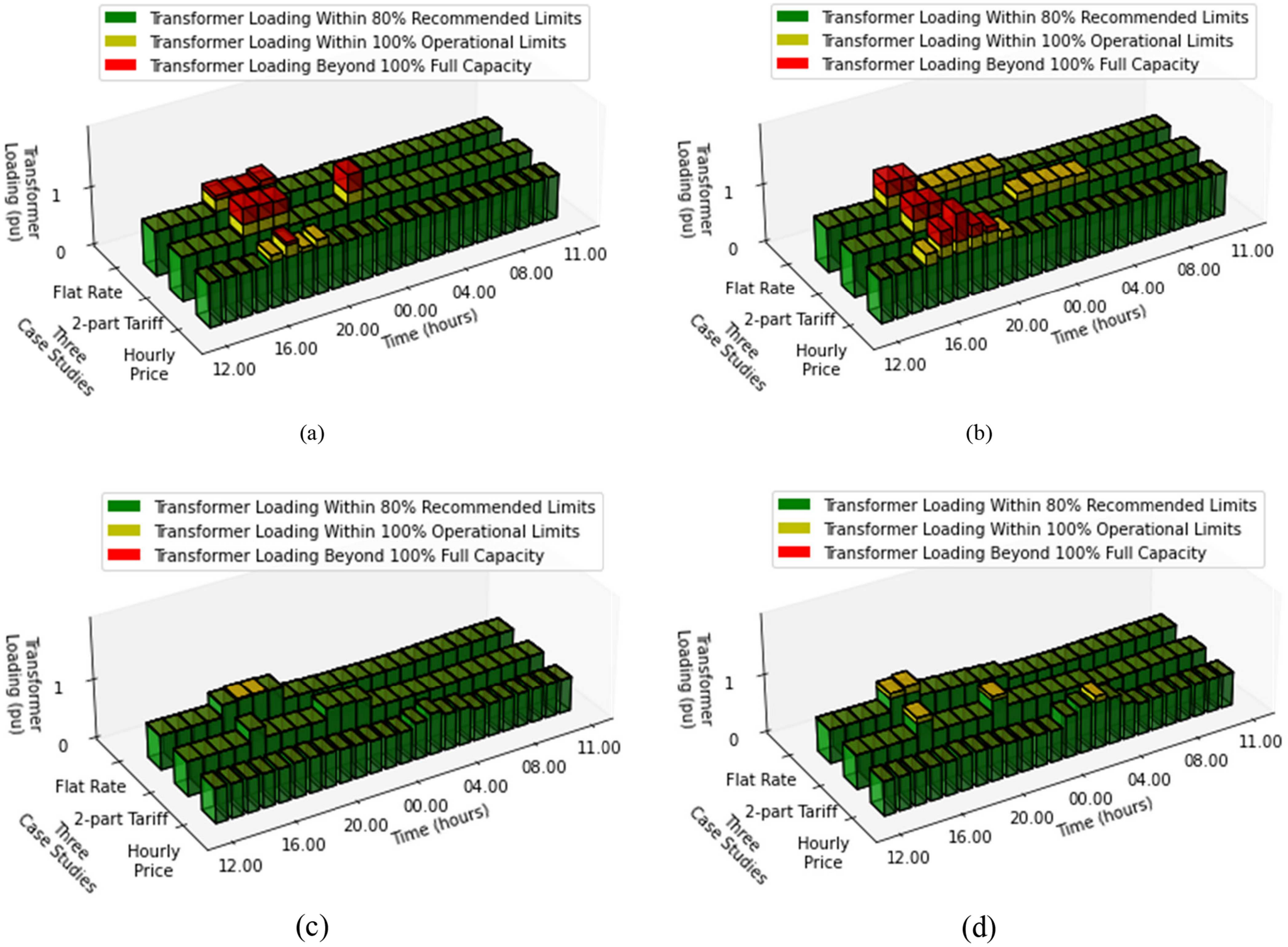
One of the most important objectives of this study is to minimize the cost of EV charging. Figure 11 illustrates the effect of cost in the case of 5% and 10% EV penetration in the summer season. The purple bars show that the charging cost for the 10% EV penetration is higher than that for the 5% penetration because more EVs are getting charged.

The charging cost in case of Flat Rate is 3024 Rs. The charging cost decreases by 5.9% to 2845.60 Rs in the case of a two-part Tariff and decreases by 18.9% to 2453.82 Rs when Hourly Price is introduced. Similarly, for the 10% penetration, the cost is 6615 Rs for Flat Rate. In the case of a two-part Tariff, the charging cost is decreased by 5.91% to 6224.75 Rs. The charging cost decreases by 28.46% to 4732 Rs in the case of Hourly Price. Time-varying, Hourly Price enables the least typical daily cost for charging the EVs, as owners try to charge EVs during the least costly hours.

Figure 12 illustrates the effect of cost in the case of 5% and 10% EV penetration in the winter season. By comparing the cost with the summer season, it is identified that in the case of hourly price charging, costs decreased in the winter season. For the rest of the two cases, the cost is the same as in the summer season because the Flat Rate and two-part tariff remain the same for both seasons.

Figure 12 illustrates the charging cost in the case of a Flat Rate is 3024 Rs. The charging cost decreases by 5.9% to 2845.60 Rs in the case of a two-part Tariff and decreases by 23.24% to 2321 Rs when the Hourly Price is introduced. Similarly, for the 10% penetration, the cost is 6615 Rs for Flat Rate. In the case of a two-part Tariff charging cost is 6224.75 Rs, which is a decrease of 5.91%. The charging cost decreases by 31.5% to 4532 Rs in the case of Hourly Price.

Furthermore, in this paper, the battery deterioration cost is not considered by incorporating the LCOS, which would provide a more holistic economic assessment.



(a) (b)

(c) (d)

FIGURE 10 | Transformer loading percentage at node 27: (a) 5% EV penetration during summer, (b) 10% EV penetration during summer, (c) 5% EV penetration during winter, and (d) 10% EV penetration during winter. EV, electric vehicle.

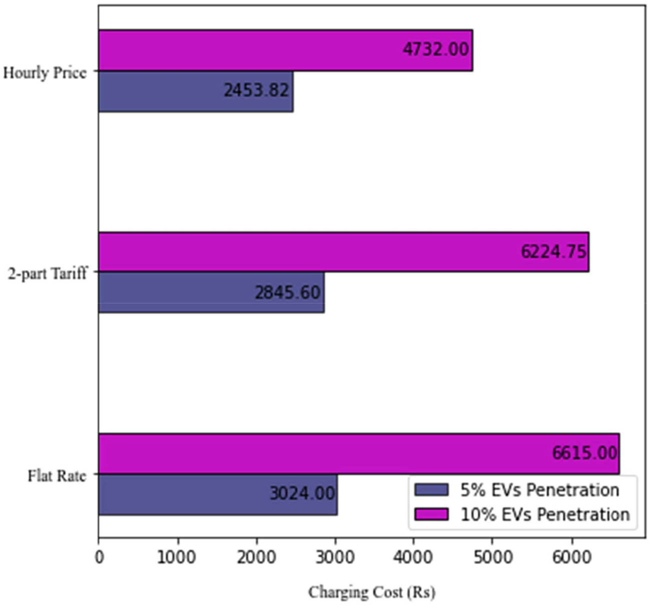


FIGURE 11 | Charging cost during the summer season. EV, electric vehicle.

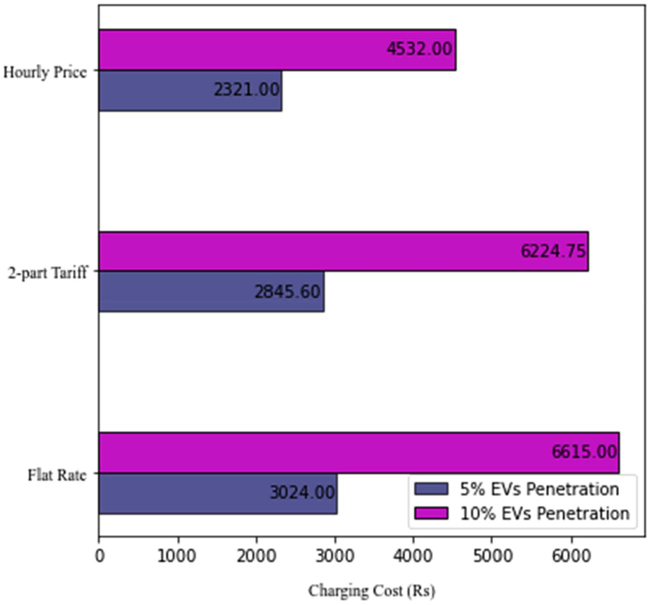


FIGURE 12 | Charging cost during the winter season. EV, electric vehicle.

5 | Conclusions and Policy Recommendations

This research demonstrates the significant potential of smart charging with dynamic hourly pricing as a policy intervention to address utility grid congestion and promote EV adoption in Pakistan. Combining an optimized energy pricing model, an agent-based energy management system, a stochastic placement model of EVs, and real distribution network data, the proposed solution offers cost savings for EV owners, mitigates grid strain during peak hours, and enables policy intervention against the uncertain growth of EVs. Therefore, this approach promotes the sustainable adoption of EVs by offering a win-win scenario for EV owners (through cost reductions), the power grid (through congestion alleviation), and energy regulators (through policy intervention).

On the basis of these findings, we recommend that policymakers in Pakistan consider implementing dynamic pricing models for EV charging. In addition, fostering collaboration between government agencies, DISCOs, and EV aggregators will be crucial for establishing the necessary infrastructure and consumer awareness programs for a successful large-scale rollout of smart-charging solutions. The updated Electric Vehicle Policy of Pakistan recognizes consumer awareness as a key enabler for EV adoption. The policy highlights coordinated public awareness campaigns by federal and provincial authorities to promote EV benefits, charging practices, and cost savings; utility and regulator-led outreach initiatives explaining tariff structures and time-based pricing; deployment of digital platforms and mobile applications to enhance price transparency and optimal charging decisions; collaboration with DISCOs, aggregators, and charging service providers for consumer education at the point of purchase and installation; and demonstration and pilot projects to strengthen public confidence in smart-charging and grid-integrated EV solutions [41].

Depending on data availability, the proposed generalized tool is capable of impact analysis on alternative distribution feeders for a wider spectrum of load profiles and consequent hourly prices. Another strength of this research is its potential to help increase the useful life of transformers under less-stressed loading conditions. While a detailed thermal aging model is beyond the scope of this study, reduced overloading duration and moderated peak loading suggest potential mitigation of transformer thermal stress. A thorough utility-wide study is essential to conclusively quantify the negative impacts of unchecked EV integration under current pricing regimes. After clustering all feeders of a DISCO and load patterns of the national grid to discover representative feeders and load patterns, an extension of our research methodology is proposed as a framework for policy intervention to support sustainable EV growth.

The proposed hourly pricing framework is discussed in the context of Pakistan's recent EVCS tariff revisions and evolving market reforms. With the gradual implementation of the Competitive Trading Bilateral Contract Market and anticipated development of a day-ahead electricity market, structured hourly pricing mechanisms will become increasingly feasible within the national regulatory framework.

Although full-scale V2G participation in ancillary service markets is deliberately excluded from the present scope, future research extension may incorporate structured V2G participation under evolving market conditions. While considering 5% and 10% EV penetration levels, higher penetration scenarios are identified as future research directions once EV market expansion accelerates. A detailed assessment of temperature-dependent SOC and SOH management under Pakistan's extreme summer conditions, including thermal-aware charging strategies to sustain high system efficiency, is proposed as a future extension of this work.

Author Contributions

Maha Iftikhar: conceptualization, data curation, methodology, validation, software, writing – original draft, writing – review and editing. **Kashif Imran:** supervision, resources, writing – review and editing, project administration, methodology, visualization, writing – original draft, investigation. **Farah Ul Ain:** data curation, methodology, software. **Abdul Kashif Janjua:** conceptualization, formal analysis, visualization, writing – original draft. **Rimsha Razaq:** methodology, software, validation. **Sohail Khan:** visualization, writing – review and editing. **Arqam Ilyas:** data curation, writing – review and editing. **Shahbaz Ul Haq:** data curation, software. **Muhammad Akmal:** supervision, writing – review and editing.

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The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this manuscript, AI-assisted language tools were used to improve clarity of certain sections (e.g., abstract and conclusion). All outputs were carefully reviewed and edited by the authors, who take full responsibility for the content of this publication.

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Data Availability Statement

Pakistan's national grid data used in this study involve detailed information about power plants, loads, and transmission networks of the National Grid Company (NGC). Since the specifics of national grids are critical energy infrastructure data, they are not publicly available, and their research use involves nondisclosure agreements. The data that support the findings of this study are available from the corresponding author upon reasonable request.

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